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Original Paper

A Globally Consistent Stress Testing Approach

Colin Ellis[1*]

[1] Department of Economics, University of Birmingham, Birmingham, UK

[*] Colin Ellis, Department of Economics, University of Birmingham, Birmingham, UK. E-mail: c.ellis@bham.ac.uk

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Abstract

This paper describes an approach for stress testing banks that is consistent across economies and geographies, in contrast to common "macro scenario" driven approaches. The latter would require economic scenarios to be both equally likely (in a probabilistic sense) and equally stressful (in a conditional loss sense) across countries in order to be comparable. The paper proposes a three-pronged approach for stressing bank solvency, which incorporates recalibrating pre-crisis Basel capital assumptions, adapting the BIS "expected shortfall" approach for securities, and using granular data for income haircuts. Loan losses are quantified using a simple "multiples" approach, starting from expected outcomes, which is derived from the pre-crisis Basel technical proposal. The approach is practical, can be more granular or conducted at a high level, depending on data availability, and offers a simple way for regulators, investors or risk assessors to compare and contrast stresses in different banking systems. Of the eight bank defaults recorded globally during 2017, this approach would have given a better "rank ordering" for seven of them, indicating the approach adds value to traditional solvency metrics.

Keywords

banks, stress tests, solvency, capital, asset quality

1. Introduction: Different Stress Testing Approaches

Since the 2007/8 financial crisis, stress testing has become a key tool for bank planning and regulatory purposes. However, there are a number of different approaches to stress testing. Prior to the 2007-8 financial crisis, implicit stress tests embedded in banks' internal capital calculations were commonly used to inform banks' capital buffers. But with many bank failures exposing these as inadequate ex post, interest in stress tests has intensified over the past decade. Key international regulatory guidance on stress testing was provided by the Basel Committee on Banking Supervision (BCBS) in 2009 (BCBS, 2009); and both the Board of Governors of the Federal Reserve System (2015) and the European

Banking Authority (2014) have prescribed recent large-scale regulatory stress tests in the US and the European Union.

A key feature of these exercises was to shift away from previous “value at risk” (VaR) approaches. VaR analysis can offer some substantial advantages, including its practical viability and conceptual attractiveness (Kupiec, 1998) and the ability to contrast multiple models and calibrations (see for example Alexander and Sheedy, 2008). But with its decline, stress tests instead became increasingly reliant on a form of scenario analysis: taking unexpected (downside) macro scenarios and estimating how those impact, via loan and securities losses, on bank capital. Lopez (2005) was one of the first to note that this mechanism would link losses to “specific and concrete” events; Jokivuolle, Virolainen and Vähämaa (2008) is one early post-crisis example of macro-driven stress testing. The popularity of these macro-driven tests extended to regulators, with some policymakers arguing they should replace the previous “Internal Ratings Based” (IRB) approach to risk-weighted capital (Tarullo, 2014). However, there is no consensus here; Borio, Drehmann and Tsatsaronis (2012) note that macro-driven stress tests are not suitable as early warning devices and would benefit from complementary information.

Concerns have also been raised about the appropriateness of the modelling framework that links macroeconomic data to bank loss rates. To start with, these frameworks were often similar to classic macro modelling and hence focused on the middle of the distribution of losses (see for example Bunn et al., 2015; and Miani et al., 2012), rather than the tail. In some instances, researchers recognized this by proposing adjustments to estimated models, for instance in Buncic and Melecky (2012). However, regulators may also have responded by picking unusually stressful scenarios in their macro-based stress tests (Ellis, 2017). More recently, there has been renewed focus on flexible models that allow these relationships to change as the analysis moves into the tail of the distribution (Covas, Rump, & Zakrajsek, 2013). These quantile models, as introduced by Koenker and Hallock (2001), may offer a better guide to stressed outcomes, but they are not yet widely employed.

However, macro-driven stress tests encounter further challenges when there is a need to compare and contrast banks in different regions or jurisdictions. Applying the same degree of stress across countries is far from simple for typical macro-driven stress tests. An assumed recession that decreases GDP by, say, 3% may not be as probable today in the US as in Indonesia; conversely, an equally probable scenario (say, with a 10% probability) may well entail a deep recession in one country and a more mild slowdown in another. Similarly, tying all countries to a single shock that is transmitted globally will not be equally stressful for every country that is affected, as the exposure to the shock and the nature of the transmission mechanism will vary from country to country.

In light of these challenges, the approach described in this paper is deliberately different: and, consequently, is not intended to be directly comparable with macro-driven stress tests. In large part, this reflects the aims and of and context in which the approach was developed, with comparability and consistency across different countries and regions being more important than country-specific risks or scenarios (which by their very nature will be heterogeneous). However, these discrepancies do not necessarily imply differences in judgments about the relative strength or viability of a bank under stressed conditions. Ultimately, as with other stress tests, this approach still aims to analyze banks' resilience under stressed conditions against a group of peers, in order to uncover potential weaknesses in the financial system.

This paper therefore describes an approach to stress testing that does not rely on downside macroeconomic scenario and, unlike most macroeconomic-driven stress tests, allows consistency and comparability of results across banks within a jurisdiction and across different jurisdictions. The rest of this paper describes each of the components in this approach that determine the stressed capital ratio. Section 2 deals sequentially with loan losses, stressing banks' income, and an approach for security losses. Section 3 then shows the results of this approach for over 70 banking systems, highlighting those more vulnerable to stressed conditions and those more resilient. Finally, the discussion in Section 4 concludes.

2. Method

2.1 Loan Losses: Starting from the Expected Case

While point forecasts represent the average or most likely outcomes given a set of macroeconomic and industry conditions, stress tests literally represent unexpected developments. As such, it is possible to draw parallels between the two: and indeed to express stressed loss rates or stressed default rates as a "multiple" of expected rates. The higher the multiple, the bigger the increase from the expected to the stressed case.

In order to exploit this link – in the context of loan losses – the analysis needs to start from an expected case. Given data limitations in many countries, one simple approach is to focus on system-level trends in asset quality, as measured by the aggregate Non-Performing Loan (NPL) ratio. As shown in past work (see for instance Buncic & Melecky, 2012, and Moody's, 2014a and 2014b), it is possible to model system-level trends in asset quality and default rates based on expected developments in the economic and financial environment, where macroeconomic data – such as real GDP, unemployment, inflation, and the exchange rate – are used to obtain forecasts for the NPL ratio.

However, econometric techniques and models differ. In general, NPL series tend to be relatively short for most banking systems (most of which are in emerging or developing economies); as a consequence, panel models may be needed to exploit cross-country patterns in the linkages between NPLs and macroeconomic variables. Wherever there is greater data availability, country-specific models can be estimated. But in either instance, the outcome from this approach is a set of projections for the aggregate or total NPL ratio in the banking system. In turn, this can be transformed into a Probability of Default (PD) given an assumption about the write-off rate of NPLs, using a simple "law of motion" approach (see Buncic & Melecky, op cit).

System-level profiles for NPL ratios can easily be transformed into NPL ratios – or PDs – for individual loan types, provided either disaggregated data on these categories are available, or assumptions are applied about the distribution of loans and asset quality. In some instances where data are more plentiful, it is possible to build specific forecasting models for individual loan types.

One important point here is that – by and large – input data are not adjusted for idiosyncratic factors above and beyond routine adjustments. Several private agencies collect arrays of balance sheet and accounting data from rated issuers, which are then adjusted to provide standardized metrics across different geographies and jurisdictions (see for instance Moody's, 2017). In principle, these input data should only be adjusted if there are clear and unambiguous grounds for doing so. For instance, an implicit assumption is often that underwriting standards are broadly consistent over time – or at least that any change is evident in metrics such as default rates or non-performing loans. This assumption is important because making sensible ad-hoc adjustments for as yet unobserved structural changes is difficult.

It is also important to note that the granularity of the data typically varies significantly from country to country and region to region. As such, simplifying assumptions are often needed. In the case of aggregate figures on, for instance, loan-to-value ratios, this implies that some banks in a system will be relatively "penalized" by using an average figure, while others will implicitly benefit. But provided the aggregates are broadly correct, these differences should average out across the system as a whole.

Where assumptions are needed for granular loan loss rates, these can be linear or non-linear provided they are consistent with the aggregate loan profile. It is also likely that individual banks may well see different PDs within the same financial system, as a result of bank-specific factors such as the quality of underwriting. To the extent to which these factors are evident in differential default data, they can also be incorporated.

This approach can then be used to calculate default rates on different loan types – and for different banks – that are consistent with a central macroeconomic scenario. However, in order to calculate loan losses estimates of loss given default (LGD) are also required.

There is a rich body of literature around LGD estimates, including many loan-specific estimates. Based on a survey of over 70 such estimates, there can be considerable variability in the appropriate LGD, depending on the type of loan (see Figure 1). A simple starting point is to use the median estimates shown; but wherever more country-specific data is available, that can also be incorporated. Similarly, differences in Loan-To-Value (LTV) ratios can also inform different LGDs for residential and commercial property.

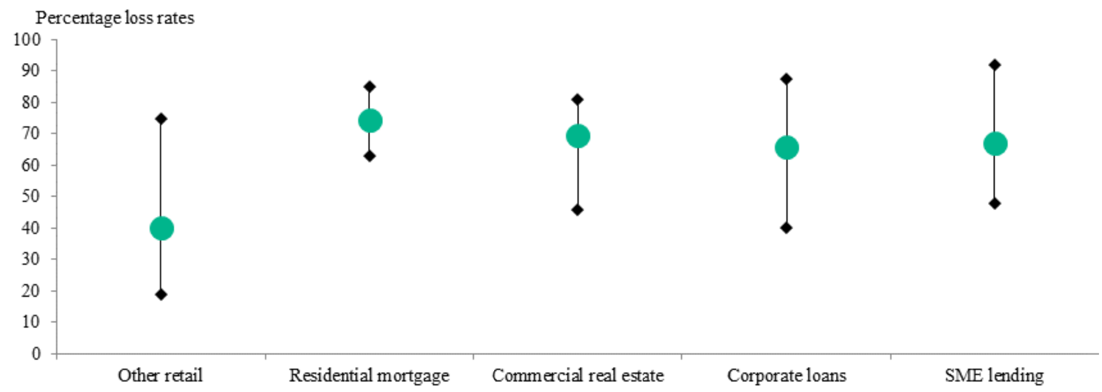

Figure 1. Range of LGD Estimates by Loan Type

Source: Author's calculations based on: Araten et al. (2004), Asarnow and Edwards (1995), BCBS (2006), Bastos (2010), Brooks and Cubero (2009), Button et al. (2010), Chalupka and Kopecsni (2009), Davydenko and Franks (2008), Dermine et al. (2006), Drehman et al. (2008), Eales and Bosworth (1998), Felton and Nichols (2012), Grunert and Weber (2009), Esaki and Goldman (2005), Felsovalyi and Hurt (1998), Jang and Kataoka (2013), Jang and Sheridan (2012), Jimenez and Mencia (2007), Memmel et al. (2011), Miroslav et al. (2006), Moody's (2000), Moody's (2004), Powell et al. (2004), Qi and Yang (2007), Wezel et al. (2012).

2.2 The Role of Multipliers: Linking Baseline PDs to Stressed PDs

The broad approach outlined above, linking central macroeconomic scenarios to credit losses, is routinely used by banks and other entities for planning and regulatory purposes. In principle, it could also be used to estimate the impact of non-central outcomes, like stress tests. However, it is difficult to ensure that those stressful macro scenarios would be comparable, because they would need to be both equally likely (in a probabilistic sense) and equally stressful (in a conditional loss sense) across all institutions and banking systems.

The alternative proposed here is to construct a simple mechanism for relating expected losses to unexpected (or stressed) losses, by adapting some of the regulatory framework first introduced in Basel II. As part of the guidance around the "Internal Ratings Based" (IRB) approach to calculating banks' risk weights, the Basel Committee sponsored the development of a specific risk-factor modelling approach that could serve as a guide to banks (Gordy, 2003). A key feature of this model was portfolio invariance: this implies that the capital required for any given loan should depend only on the risk of that loan, and not on the portfolio that it is added to. Using this framework, banks could then calculate expected and unexpected losses associated with each credit exposure, because the modelling process nests an estimation of the entire distribution of potential losses: further details are provided in BIS (2005).

The regulatory mapping implied in this research was derived from a version of the single asset model proposed by Merton (1974), and as such depends on the properties of the normal distribution, which is assumed to capture the change in value of a borrowers' assets. However, this distributional assumption could be relaxed in principle. It also depends upon the correlation assumed between different borrowers, which can again vary.

The broader perspective is that this modelling approach can define a relationship between the expected (central) losses banks face, and the unexpected (stressed) losses in the tail of the distribution. This "multiple" relationship was entirely defined – if implicit – in the original Basel calibrations, and varies with the degree of expected (central) loss: illustrative multiple curves are shown in Figure 2. The algebraic derivations are reported in Appendix 1.

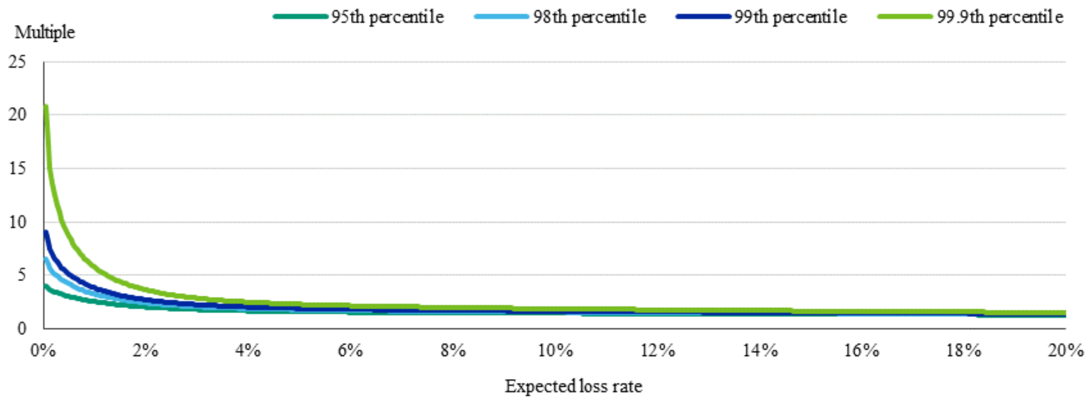

Figure 2. Stress "Multiples" Implied by Basel II Capital Approach

Source: BIS (2005) and author's calculations.

The downward slope of the curves in Figure 2 has a simple interpretation: it implies that, when banks are already seeing high losses, the relative distance between the expected and stressed outcomes may be small. When an economy is in recession, and real incomes are falling, financial distress among borrowers is already likely to be running at high levels. In these circumstances, banks' impairment rates are already likely to be high. As such, the distance to an implicit stress scenario – a deeper recession – is likely to be relatively low, at least compared with a different economy that is not already in recession. In contrast, banks' impairment rates are likely to be relatively low when an economy is growing robustly, and the distance to a stress scenario may be relatively high.

The convexity of the multiple curves is consistent with the fact that initial deteriorations in asset quality can be quite sharp when unexpected losses first start to mount; but any acceleration in loan impairments is likely to be lower if the economy is already in recession. This simple adaptation of the Basel approach therefore offers another means of constructing unexpected loss rates, or stressed credit losses, for banks. One particularly appealing feature of this approach is that, in principle, the multiple curves implied by the regulatory framework are global in nature, as the original technical work was, and hence can be applied to different banking systems and countries.

In principle, these multiple curves can be used to generate stressed loss outcomes, obviating the need for a set of globally consistent macro scenarios for individual countries. However, they also suffer from obvious shortcomings, notably the poor performance of capital risk weights during the financial crisis.

This suggests that the original asset risk models proposed by Basel need recalibrating. Properly assessing this would require estimates of pre-crisis expectations for credit losses, which are not readily available. But two simple proxies are easy to construct: the first is based on the assumption that expected losses were equal to the pre-crisis series average; for the second, we can assume that expected losses followed a random walk, implying they would be the same as realized losses in the previous year.

Armed with these pseudo "real time" estimates of expected losses, it is possible to examine what the actual loss outturns during the crisis implied in terms of multiples, compared with the original Basel calibrations. Table 1 presents results for the US, where data are most granular and coverage is good.

Table 1. US Banks' Crisis Experience and Basel-Implied Multiples

	Highest implied multiple during 20016-2011		Basel-implied multiples			
	"Series average" expected loss	Random walk expected loss	90th percentile	95th percentile	98th percentile	99th percentile
Corporate loans	2.98	2.79	2.82	3.93	5.56	6.89
Real estate loans	8.00	6.60	2.35	3.31	4.76	5.99
Credit cards	2.51	1.80	1.54	1.75	2.02	2.21

Source: Federal Reserve and author's calculations.

The results here suggest that the Basel models may not have been very misleading in the recent crisis for corporate loans, and to a lesser extent credit cards, depending on the implicit likelihood assigned to the financial crisis. The highest observed multiple for corporate loans, of 2.98, was well within the tail risks implied by the original calibrations. Unsurprisingly, the most obvious difference is for real estate, where the multiples observed during the crisis were much higher than the pre-crisis models suggested. But this offers an obvious recalibration approach: parameters from the original Basel specification can be adjusted until the implied multiples match the observed outcomes at some given percentile. For instance, given the implied multiple observed during the crisis was as high as 8 for US real estate loans, but the 99th Basel-implied percentile was only around 6, the Basel approach can be recalibrated to generate in higher multiples for real estate loans.

This approach therefore offers a simple but consistent mechanism for constructing stressed loss rates on different lending types across banks in different systems.

2.3 Income Haircuts: Using the Unconditional Distribution

Bank stress tests are about more than loan losses on credit portfolios, however. One key component of any stress test relates to the treatment of banks' income. Profitability is a key determinant of bank solvency; the ability to internally generate capital, via retaining earnings, can be an important mitigating factor against emerging stresses. At the same time, it is unlikely that earnings will be unaffected by such stresses, and may fall as conditions deteriorate.

However, it is difficult to estimate stable relationships between banks' income and macroeconomic developments over time. In part, this reflects a relative lack of granular income data over a long time period. In the absence of these relationships, bank income is stressed based on the distribution of past changes in Pre Provision Income (PPI). Fortunately, some data providers collect information on PPI across hundreds of banks each year, allowing us to build up a picture of the global distribution of changes in PPI and its components. Figure 3 plots the distribution of two-year changes in PPI for a sample of around 700 banks between 2007 and 2015.

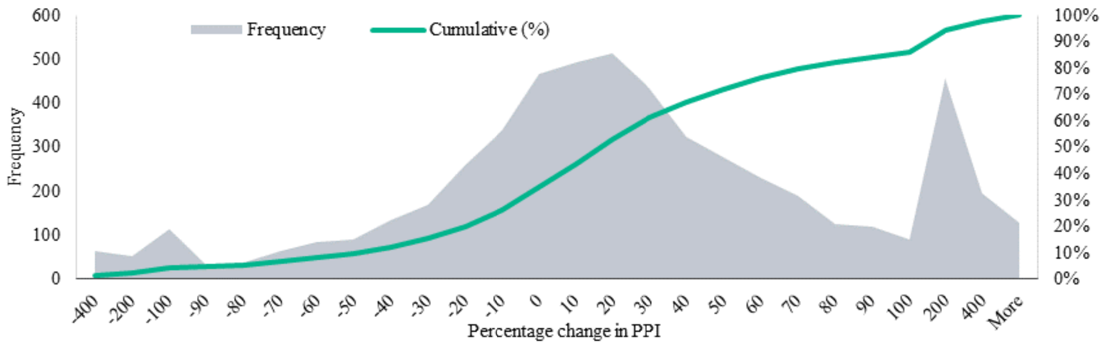

Figure 3. Global Distribution of Two-Year Changes in Banks' PPI

Source: Moody's (2016b).

Using these data, we can estimate income haircuts for use in stress tests, based on tail outcomes. The underlying assumption here is that the data distribution shown in Figure 3 is a reasonable representation of the true, unobserved unconditional distribution of changes in PPI: that is, we assume that the data capture sufficient heterogeneity across and within regions and over time. However, it would be possible to modify this distribution, depending on what assumptions are deemed appropriate. In practice, changes in PPI (and its components) will reflect a range of factors, including country risk, sector risk and idiosyncratic risk. But, in the absence of a model that can consistently account for all of these across countries and over time, this assumption provides a simple and practical way to proceed. Furthermore, it does not seem an unreasonable assumption given that the sample includes a diverse sample of banks (commercial, investment, development, universal banks; big and small banks), across regions (advanced and emerging economies) and it includes data throughout the economic cycle (including the severe recession in 2009 and the uneven recovery thereafter).

Based on this assumption, the observed distribution can be used to generate income haircuts for banks, which can be applied in stress tests. In particular, depending on the desired degree of stress to apply – and, consistent with the multiples approach to loan losses, this can be defined as a percentile of the distribution – an income haircut that is consistent with the observed distribution can be employed. For instance, in a "1 in 25" stress test, the income haircut would be informed by the 4th percentile of the distribution of changes in PPI.

In practice, this approach can be employed for different components of banks' income, such as net interest income and non-interest income, rather than focus on aggregate PPI. Importantly, however, income haircuts are not applied to trading income: this is covered under the securities stress approach, and hence would "double count" stresses if also applied here. Similarly, a simplifying assumption in several stress tests is that operating expenses are constant, and that the impact of management actions is limited to pre-announced measures. However, if these assumptions – or indeed the observed distribution of income changes – is not representative, then either the assumptions, or the distribution of income data, can be adjusted to inform different approaches. The main goal here is to demonstrate that the approach again offers a simple and consistent mechanism to consistently stress banks around the globe, based on the observed data.

2.4 Securities Losses: A Differentiated Approach

The third key component in this stress testing approach is to impose losses on banks according to their securities holdings. For many banks around the world, securities represent a relatively small component of the total balance sheet, compared with loans. But despite this, securities can play a significant role in stress tests.

In principle, there are three broad categories of securities holdings (and a residual "other" category). The first are securities that are Held To Maturity (HTM). In essence, banks will only realize losses on these securities if they default. The second are securities on the trading book (TRD). And the third are securities that are available for sale (AFS). Given the different nature of these three groups, a differentiated approach for stress testing is required.

For HTM securities, where a published credit rating exists, it is simple to apply published loss rates associated with that published rating (see Moody's, 2016a). However, in a stressed scenario there would likely be some deterioration in ratings from their pre-stress levels. This risk can be incorporated using published transition matrices for ratings. For instance, for a two-year stress, and again focusing on a "1 in 25" event, the 4th percentile of rating transitions can inform potential deteriorations in credit quality.

Based on published data, in this instance that would be broadly consistent with a three-notch rating downgrade; so a "1 in 25" stress for bank with bonds rated Baa2 (on Moody's scale) would imply a downgrade to Ba2 (Table 2). This in turn corresponds to a published two-year (idealized) loss rate of 1.9%. Where published ratings are not available, benchmarks can be constructed based on close peers or assumptions; for instance, that the average rating of corporate bonds held by a bank matches the average rating in the region or country where the bank is domiciled.

Table 2. Two-Year Cumulative Rating Transition Rates

	Two-year rating horizon						
Initial rating	Ca, C + Default	Caa	B	Ba	Baa	A	Aa
Aaa	0.0%	0.0%	0.0%	0.0%	0.2%	1.8%	***17.2%***
Aa	0.1%	0.1%	0.2%	0.5%	1.8%	***18.1%***	98.5%
A	0.2%	0.3%	0.7%	1.9%	***12.0%***	94.8%	99.9%
Baa	0.6%	0.9%	2.5%	***9.1%***	91.0%	99.5%	99.9%
Ba	3.0%	***4.6%***	17.4%	86.1%	98.8%	99.9%	100.0%
B	***10.6%***	21.6%	88.8%	98.3%	99.6%	99.9%	100.0%
Caa	***24.7%***	84.0%	98.4%	99.7%	99.9%	100.0%	100.0%
Ca, C	***74.9%***	91.0%	98.6%	99.9%	100.0%	100.0%	100.0%

Note. Transition probabilities are cumulative from the left-hand column to the right-hand one. The rating category that nests a 4% cumulative downside outcome (consistent with a "1 in 25" stress) is shown in bold italics.

Source: Moody's (2016c).

The treatment of securities on the trading book (TRD) should necessarily be different. In principle, these are not securities that banks will necessarily hold for long periods of time, so imposing large credit losses that may not crystallize for the bank may be inappropriate. At the same time, the trading book is affected by market risk in a much more immediate fashion than securities that are held to maturity. The process for stressing these securities is an adaptation of the "expected shortfall" approach outlined by the Basel Committee (BCBS, 2016). Essentially, this approach estimates loss rates on securities for a given holding period, which are calibrated using losses observed in a severe preceding year. Using past data for equity and bond indices that cover the global financial crisis in particular – which tends to represent the most severe 12-month period in recent history – loss rates for different types of securities can be calculated. Where data limitations are prohibitive and do not allow country-specific loss rates to be calculated, regional loss rates can be constructed, or loss rates from comparable countries can be used. Illustrative examples of loss rates are presented in Figure 4; further details on the expected shortfall approach are provided in Appendix 2.

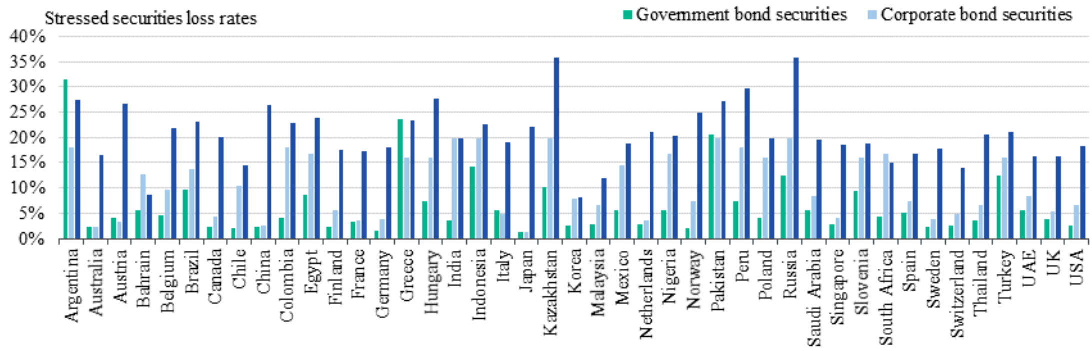

Figure 4. Two-Year Stressed Loss Rates on Securities from "Expected Shortfall" Approach

Source: Moody's (2016c).

The third category of securities are those that are Available For Sale (AFS). The treatment of equity securities on the AFS book is assumed to follow that of TRD securities, as a reflection of the fact that the risk associated with equity is best gauged using a market risk measure rather than a credit risk one. However, AFS bonds are stressed following the HTM approach based on ratings (with the same notching for stress outlined earlier), since this better reflects credit risk. Unrealized gains or losses from AFS securities do not impact on net income, but are accumulated as part of other comprehensive income; they impact capital and equity measures when realized through the profit and loss statement.

In addition to the treatment of loan losses, pre-provision income and securities losses, stress testing approaches generally encompasses a number of other assumptions for factors such as management actions, dividends and risk-weighted assets. These are detailed in previous research (Moody's, 2016c), and often rely on simple assumptions; in this stress testing approach, the three key components are those outlined above.

Taken together, these assumptions and methods form a consistent approach for stress testing banks' solvency metrics globally, and one that is not dependent on specific macroeconomic scenarios. However, it is important to note that no stress test provides a rigid definition of how banks' capital positions will necessarily respond to unexpected developments. Instead, they can offer useful signposts and benchmarks that can inform judgments about the banks' resilience to future uncertainties.

3. Stress Tests in Action: Identifying Banks Vulnerable to Shocks

In principle, the stress testing approach outlined above can be calibrated to different levels of stress – corresponding to different percentiles in the tails of the associated distributions – and over different time periods; the degree and duration of the stress can vary. For the purposes of this research, results are presented based on a "1 in 25" event, occurring over a two-year horizon.

The typical impact of this calibration on bank solvency metrics is substantial. Based on stress tests run at the end of 2016, the median banking system would see its Tangible Common Equity (TCE) ratio go down by near 8 percentage points (pp, from a starting level of around 13%) and the problem loan ratio up by 8.5pp (from near 4%). Losses in this scenario would be very significant, with a net loss of around 2.7% of tangible assets, compared with actual net income for the median system of around 1% of tangible assets in 2016.

However, by design, this stress test is also able to transform the risk factors that identified in the stress test into significant differences in results. Figure 5 shows the impact of the stress test on capital (the difference between the initial TCE in 2016 and the stressed capital ratio) for a sample of 78 banking systems. As can be seen, there is a wide dispersion around the median. Within each group, there are notable exceptions, but in general banks in Latin America, the Commonwealth of Independent States and Africa suffer relatively more in the stress test, with larger deteriorations in capital. Capital is not the only outcome from the stress test: metrics for asset quality and profitability, in particular, can also be constructed. Figure 5 demonstrates that the stress testing approach does imply significant variation across many different banking systems, thereby offering new information about relative bank resilience.

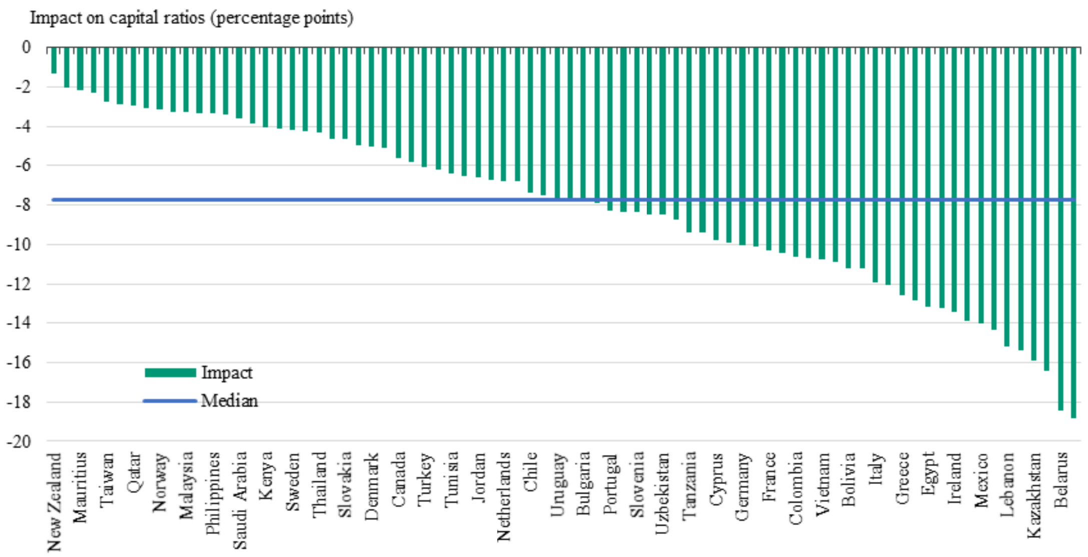

Figure 5. TCE Ratio Results across Banking Systems from Stress Testing Approach

Source: Moody's.

Furthermore, that new information appears to have predictive properties, albeit based on a very small sample of data. The first set of results from the full stress test presented here were compiled in late 2016. During the course of 2017, there were eight bank defaults identified by Moody's across its rated universe. And for seven of these eight, the capital metrics resulting from the stress test were worse, in terms of the rank ordering of banks, than the backward-looking data used to inform bank ratings (Figure 6). This means that the stress test outperformed the base case, in terms of rank-ordering prospective bank failures, in seven out of eight cases.

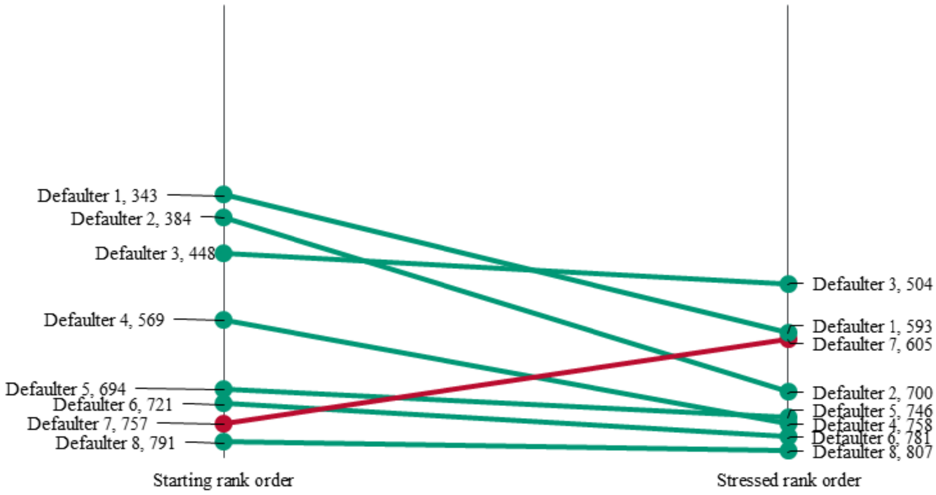

Figure 6. Starting Distribution of Banks Versus Stress Test Results

Note. All banks are rank ordered (out of 807 total) for both starting capital and post-stress tests outcomes. Banks that subsequently defaulted are shown: green indicates the rank ordering under the stress test was lower (i.e., better); red indicates it was higher (i.e., worse).

Source: Moody's and author's calculations.

4. Discussion

Most bank stress tests tend to be scenario-driven exercises, relying on some form of macroeconomic narrative underpinning the loss rates that are applied and the solvency outcomes that ensue. Within individual economies, this approach can at least be comparable across different financial institutions; at the same time, it is important to note that differently designed scenarios that focus on different sectors or exposures will still have a variable impact across banks, depending on individual institutions' exposures. It is also worth bearing in mind other criticisms of macro-based stress tests, and the fact that any form of test is unlikely to be a good guide to how a risk actually crystallizes.

These considerations imply that, when we want to compare the resilience of different institutions around the world, it may be difficult to construct consistent and comparable macro-driven stress tests that are both equally probably and equally stressful, in a conditional loss sense.

In light of this challenge, this paper has described an alternative approach to bank stress testing, building on past work by BIS regulators. A key aim of the Basel framework is that is offers a consistent approach to calculating capital requirements, which in turn relate to unexpected losses; but the calibration and application of the Basel rules were found wanting during the crisis, in the sense that capital requirements proved to be far too low to cope with the losses that did crystallize.

By recalibrating the pre-crisis credit models proposed by Basel, to account for the experience during the 2007/8 financial crisis and subsequent years, it is possible to construct a simple and consistent approach for calculating stressed loan losses, using multiples of expected losses. These multiples have a simple and intuitive interpretation. Combined with assumptions about income haircuts and securities losses, informed by crisis-era data and new analysis from regulators, this offers a different approach to stress testing that more readily allows for global comparisons. That, in and of itself, means the stress testing approach described herein can add value to existing exercises conducted around the world, both by policymakers and private institutions. Furthermore – although the sample of ex-post outcomes is very small so far – this global stress testing approach appears to add value to rank orderings of credit risk. As such, it offers a useful tool to practitioners and policymakers alike.

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Appendix 1: Relating stressed losses to expected losses

Under the Basel II regulatory approach (see BIS, 2005), banks were required to hold supervisory capital charges based on an assessment of unexpected losses. Algebraically, the formula for this capital requirement (*K*) can be expressed as:

$$K = \left[LGD * N\left\{\left(\frac{1}{1-R}\right)^{0.5} * G(PD) + \left(\frac{R}{1-R}\right)^{0.5} * G(P)\right\} - PD * LGD\right] * \omega \qquad (1)$$

where *N* represents the standard normal distribution, *G* the inverse standard normal distribution, *P* represents the percentile at which the unexpected losses are evaluated, *R* represents the correlation between the asset values of different borrowers, and *ω* represents an adjustment to take account of varying loan maturities. Under the Basel II approach, unexpected losses are assessed at the 99.9th percentile (P = 0.999), representing extreme tail losses.

Simply put, this expression defines the unexpected loss as the difference between the expected loss and the tail (stressed) loss given assumptions about the nature of potential losses. The 'unexpected' loss is the difference between the central VaR and the expected loss.

To model the correlation of borrowers' asset values, the Basel approach differentiates between different types of lending. However, the correlation is typically described as a function of the Probability of Default (*PD*), and correlations are assumed to decrease as PDs increase. Hence for non-mortgage retail exposures, the Basel approach specifies the following correlation formula:

$$R = 0.03 * \frac{1-\exp(-\gamma * PD)}{1-\exp(-\gamma)} + 0.16 * \left[1 - \frac{1-\exp(-\gamma * PD)}{1-\exp(-\gamma)}\right] \qquad (2)$$

Where the highest and lowest correlations are 16% and 3%, respectively. The parameter γ determines the speed with which the correlations decrease as PDs increase: in the case of "other retail", the 2005 Basel calibration is 35, but for "corporate lending" it is 50.

Another important factor in the risk weighting formula is the maturity adjustment. As longer-term credits are riskier than short-term credits, the Basel approach explicitly increases the capital requirement with maturity. Based on empirical analysis, the Basel maturity adjustment is specified as:

$$\omega = \frac{1+(m-2.5)*b(PD)}{1-1.5*b(PD)} \qquad (3)$$

Where *m* represents maturity. The right-hand terms in this expression are smoothed maturity adjustments based on regression analysis of default rates, as defined in the Basel approach:

$$b(PD) = [0.11852 - 0.05478 * \log(PD)]^2 \qquad (4)$$

Importantly, this maturity adjustment is only applied to corporate risk weights in the Basel approach; retail risk weight functions do not include maturity adjustments.

The focus here is on unexpected losses, rather than capital requirements, but under the Basel approach the two are equivalent. As such, unexpected losses (UL) can be defined as:

$$UL = \left[N\left\{\left(\frac{1}{1-R}\right)^{0.5} * G(PD) + \left(\frac{R}{1-R}\right)^{0.5} * G(P)\right\} - PD\right] * LGD * \omega \qquad (5)$$

By definition, this unexpected loss is the difference between the central VaR and the expected loss; so in order to calculate the stressed loss (SL) the expected loss needs to be added back in:

$$SL = UL + PD * LGD \tag{6}$$

Finally, combining (5) and (6) and defining the multiple as the ratio of stressed to expected losses gives the formula for the multiple curve:

$$Multiple = 1 + \frac{\left[N\left\{\left(\frac{1}{1-R}\right)^{0.5} * G(PD) + \left(\frac{R}{1-R}\right)^{0.5} * G(P)\right\}\right] * \omega}{PD} \tag{7}$$

The multiple is therefore a function of the (Basel) asset correlations (*R*), the Probability of Default (*PD*) and a judgment about how far into the tail of the loss distribution the stress should be (*P*).

Appendix 2: Adapting the Expected Shortfall approach for securities stresses

The approach described in this paper for stress testing trading securities is inspired by the revised standards for minimum capital requirements for market risk set by the Basel Committee in January 2016, consistent with the fundamental review of the trading book (see BCBS, 2016). In its proposal, the Basel Committee implements a shift from value-at-risk (i.e., the maximum losses within a certain confidence level) to Expected Shortfall (ES), which is the expected loss conditional on a loss greater than a defined percentile of the loss distribution. The stressed calibration is defined following this Basel approach, using the proposed 10-day holding period to calculate losses. The Basel ES approach allows for liquidity adjustments to this holding period, but the limited availability of public data makes this adjustment quite challenging, so the 10-day holding period is maintained as a baseline.

In the Basel approach, capital charges are calculated taking into account risk factor sensitivities (for instance, delta, vega and curvature) within a prescribed set of risk classes. In the stress tests described herein, a simplified approach is used due to lack of granular data: the ES is calculated using a relevant index for each security that captures the relevant market risk (e.g., an index of high-yield corporate bonds in emerging Asia for a corporate bond in the Philippines). As set out in the Basel approach, returns on securities are calculated for the 10-day holding period and the most stressed year (252 trading days) is identified in the past 10 years, as defined by the highest standard deviation. The distribution of 10-day returns can then be calculated for that 252-day period: and the appropriate percentile of the distribution can be selected, consistent with loan loss and income assumptions (for instance, with the 4th percentile of that distribution corresponding to the “1 in 25” calibration). In principle, this choice of percentile can be varied in the same manner for both securities and loan losses and income. The average of all the 10-days returns (which are typically negative by selection) up to that percentile is then the loss rate that is applied to the trading book.